Neural Language Priming

Marten van Schijndel Department of Linguistics, Cornell University February 01 2022

What are effective language processing representations?



We can explore the space using priming

What is priming?

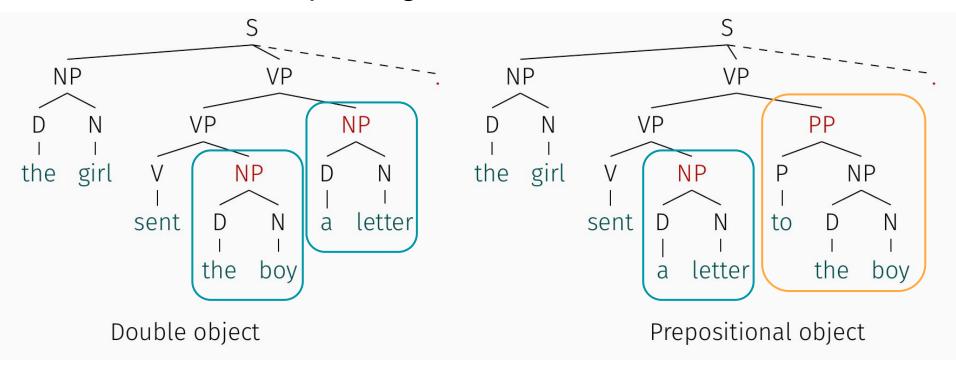
```
... cassowary ...
```

Cassowaries ...

... Just like a cassowary!

... cassowary ...

What is structural priming?



What is structural priming?

A rockstar sold some cocaine to the undercover agent.

. . .

The girl sent a letter to the boy.

What is structural priming?

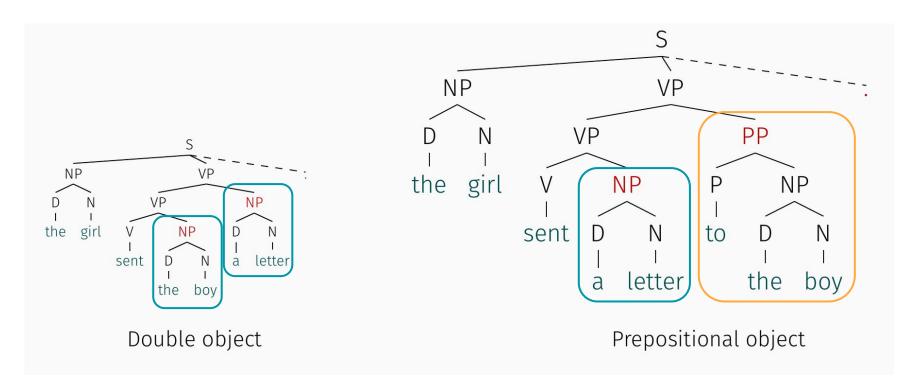




Image by @hassaanhere on Unsplash

Why expect this to work with NNs?

NNs require large amounts of data to train

Small amounts of training data should skew distributions according to sensitivity without wholly retraining them

Neural language models can be primed



Tal Linzen

A Neural Model of Adaptation in Reading

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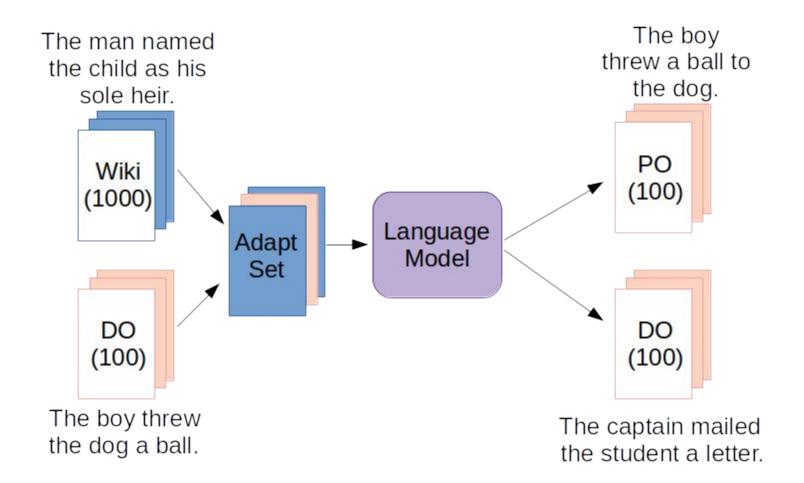
Proceedings of EMNLP 2018

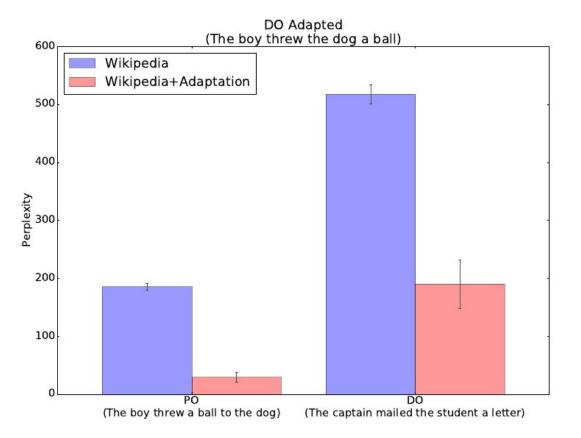
Adaptation priming algorithm

- 1) Test on a sentence
- 2) Update weights by fine-tuning on that sentence
- 3) Repeat on remaining sentences

Conclusions

- Better linguistic accuracy
- Better psycholinguistic accuracy







Grusha Prasad



Tal Linzen

Using Priming to Uncover the Organization of Syntactic Representations in Neural Language Models

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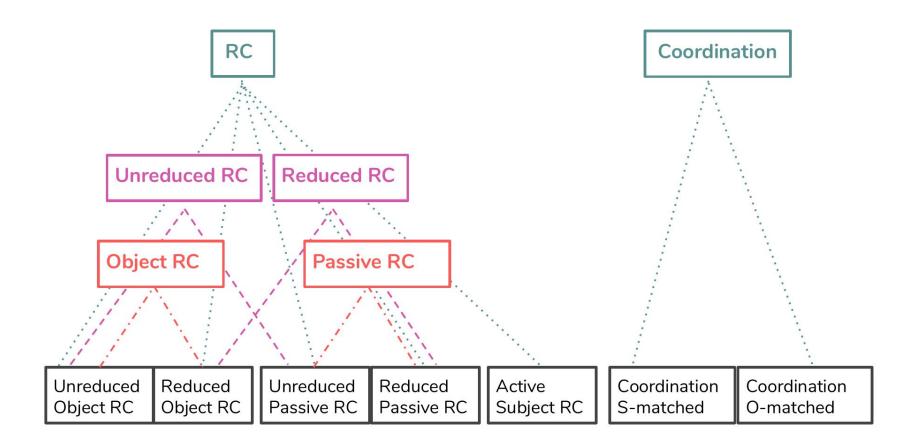
Proceedings of CoNLL 2019

Abstract structure	cture Example		
Unreduced Object RC	The conspiracy that the employee welcomed divided the beautiful country.		
Reduced Object RC	The conspiracy the employee welcomed divided the beautiful country.		
Unreduced Passive RC	The conspiracy that was welcomed by the employee divided the beautiful country.		
Reduced Passive RC	The conspiracy welcomed by the employee divided the beautiful country.		
Active Subject RC	The employee that welcomed the conspiracy quickly searched the buildings.		
PS/ORC-matched Coordination	The conspiracy welcomed the employee and divided the beautiful country.		
ASRC-matched Coordination	The employee welcomed the conspiracy and quickly searched the buildings.		

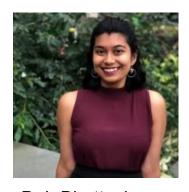
Abstract structure	Example
Unreduced Object RC	The conspiracy that the employee welcomed divided the beautiful country.
Reduced Object RC	The conspiracy the employee welcomed divided the beautiful country.
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Abstract structure	Example
Unreduced Object RC Reduced Object RC	The conspiracy that the employee welcomed divided the beautiful country. The conspiracy the employee welcomed divided the beautiful country.
Unreduced Passive RC Reduced Passive RC	The conspiracy that was welcomed by the employee divided the beautiful country. The conspiracy welcomed by the employee divided the beautiful country.
Active Subject RC PS/ORC-matched Coordination	The employee that welcomed the conspiracy quickly searched the buildings. The conspiracy welcomed the employee and divided the beautiful country.
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Abstract structure	Example
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PS/ORC-matched Coordination ASRC-matched Coordination	The employee that welcomed the conspiracy quickly searched the buildings. The conspiracy welcomed the employee and divided the beautiful country. The employee welcomed the conspiracy and quickly searched the buildings.



Priming reveals abstraction depth



Deb Bhattacharya

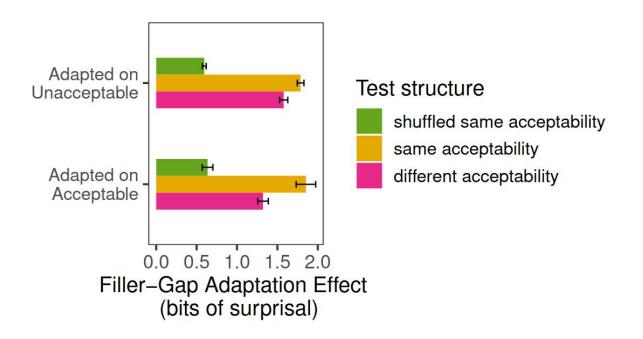
Filler-gaps that neural networks fail to generalize

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Proceedings of CoNLL 2020

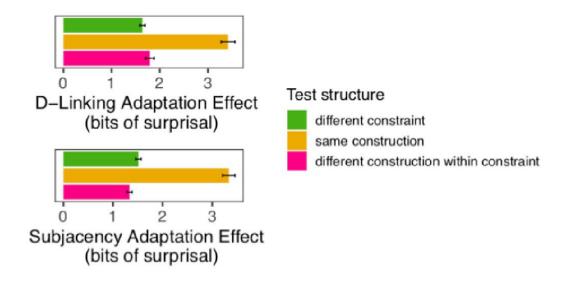
Construction	Examples
Adjunct island Wh- island Subject island	*What did you go home because you needed to do? *Whom did Susan ask why Sam was waiting for? *Who is that went home likely?
Left branch island Coordinate structure island	*Whose does Susan like account? *What did Sam eat and broccoli?
Complex NP island	*What did you hear the claim that Fred solved?
Object extraction	Who is it probable that Bill likes?
Non-bridge verb island	*How did she whisper that he had died?

Networks encode broad FG existence



Construction	Examples	L	S	Е	D
Adjunct island	*What did you go home because you needed to do?	_		_	
Wh- island	*Whom did Susan ask why Sam was waiting for?		-		(+)
Subject island	*Who is that went home likely?	-	-	-	
Left branch island	*Whose does Susan like account?		-		(+)
Coordinate structure island	*What did Sam eat and broccoli?			+	
Complex NP island	*What did you hear the claim that Fred solved?		_		
Object extraction	Who is it probable that Bill likes?	+		+	(+)
Non-bridge verb island	*How did she whisper that he had died?	?	?		

Networks do not encode abstract FG constraints



Priming reveals constraint-like interactions



Forrest Davis

Uncovering Constraint-Based Behavior in Neural Models via Targeted Fine-Tuning

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Proceedings of ACL 2021

Who is terrifying?







Who is terrifying? Sally

Who is terrifying?



Who is terrifying? Mary

Implicit Causality

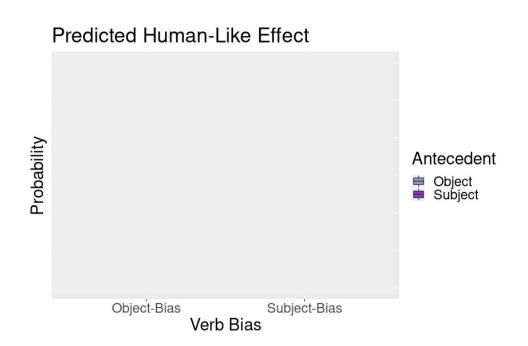
- Some verbs are subject-biased
 - frightened, amused, astonished, enraged

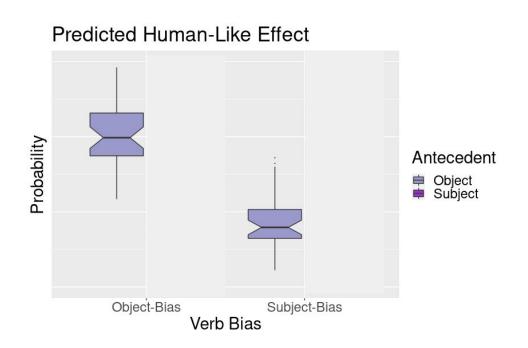
- Others are object-biased
 - feared, admired, loved, hated

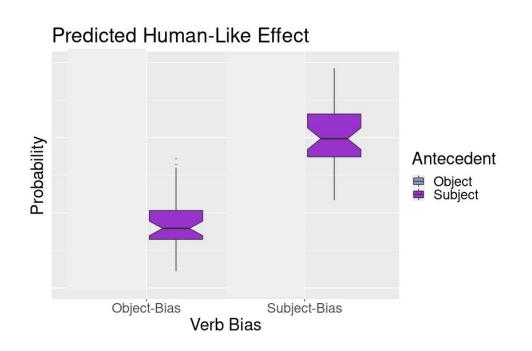
English

the man admired the woman because [MASK] was there.

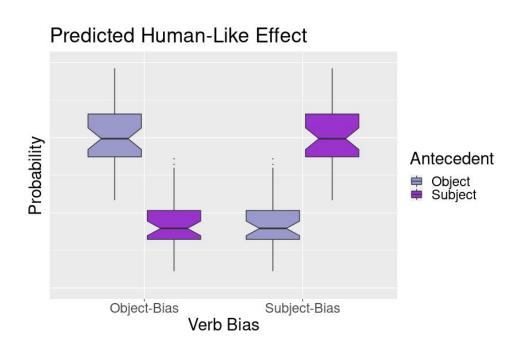
- ~300 IC verbs from Ferstl et al. (2011)
- bert-base-uncased (HuggingFace)
- Expect higher probability for pronouns agreeing with the bias (admire = object-biased)
 - \circ P(she) > P(he)



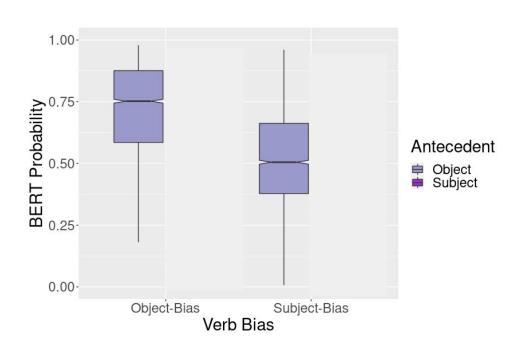




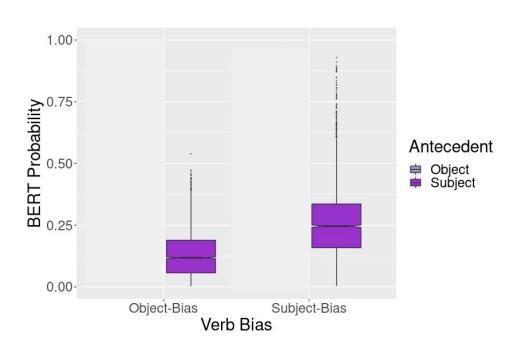
Evaluating English BERT for IC behavior



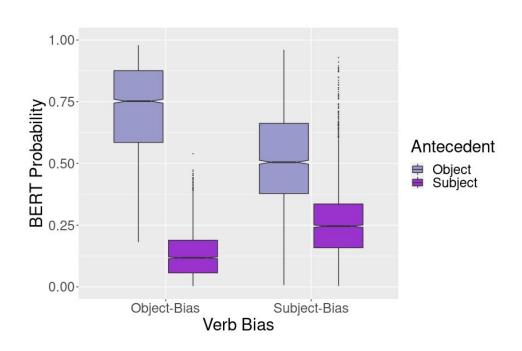
English BERT shows IC behavior



English BERT shows IC behavior



English BERT shows IC behavior



IC is attested cross-linguistically

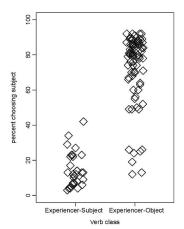


Figure 6. Degree of subject-bias for English emotion verbs reported in Ferstl, Granham, Manouilidou (in press).

English

from Hartshorne et al. (2013)

Dutch

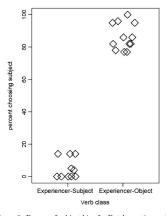


Figure δ . Degree of subject-bias for Dutch emotion verbs reported by Koornneef and van Berkum (2006).

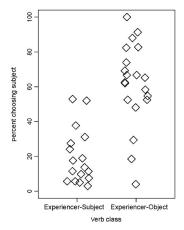


Figure 7. Degree of subject-bias for emotion verbs in Spanish as reported by Goikoetxea et al. (2008).

Spanish

Italian

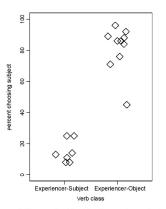


Figure 9. Degree of subject-bias for emotion verbs in Italian as reported by Mannetti and de Grada (1991).

Spanish & Italian

Evaluating Spanish BERT for IC behavior

el hombre admiró a la mujer porque [MASK] estaba allí.

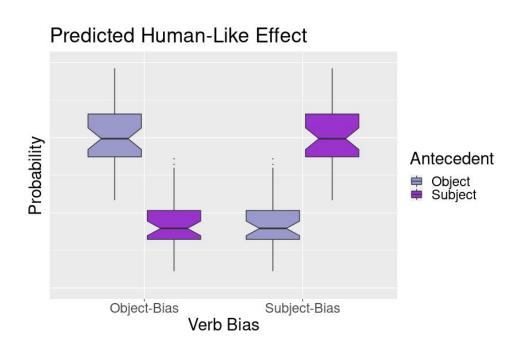
- 100 IC verbs from Goikoetxea et al. (2008)
- 14 pairs of M/F nouns (balanced for gender, position)
- dccuchile/bert-base-spanish-wwm-uncased (aka BETO; HuggingFace)
- Expect higher probability for pronouns agreeing with the bias (admiró = object-biased)
 - P(ella) > P(él)

Evaluating Italian BERT for IC behavior

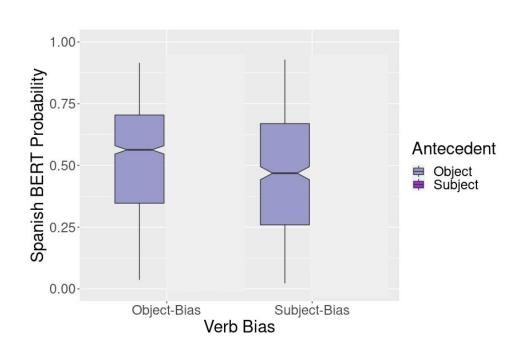
l'uomo lusinga la donna a causa del tipo di persona che [MASK] è.

- 40 IC verbs from Mannetti and de Grada (1991)
- 14 pairs of M/F nouns (balanced for gender, position)
- dbmdz/bert-base-italian-uncased (HuggingFace)
- Expect higher probability for pronouns agreeing with the bias (lusinga = object-biased)
 - P(lei) > P(lui)

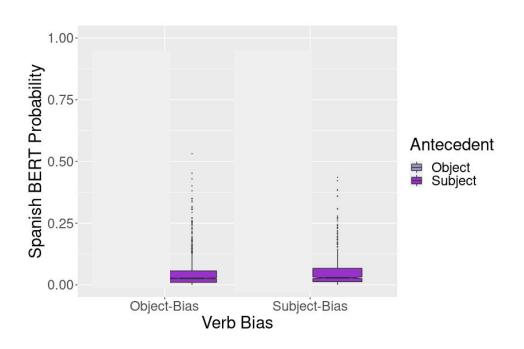
Recall what we want to see



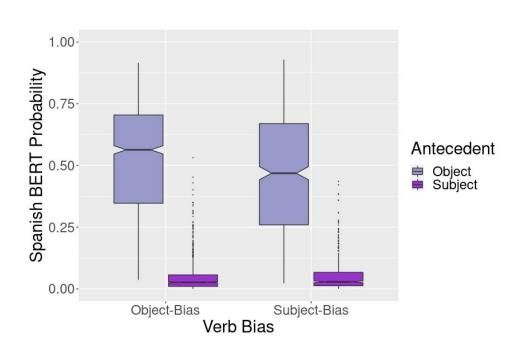
Spanish BERT partial? IC behavior

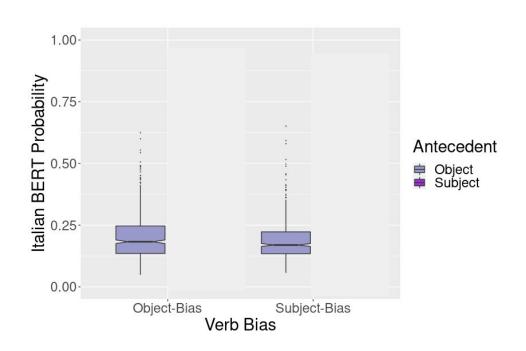


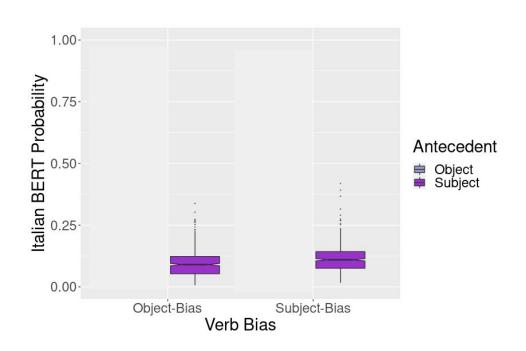
Spanish BERT partial? IC behavior

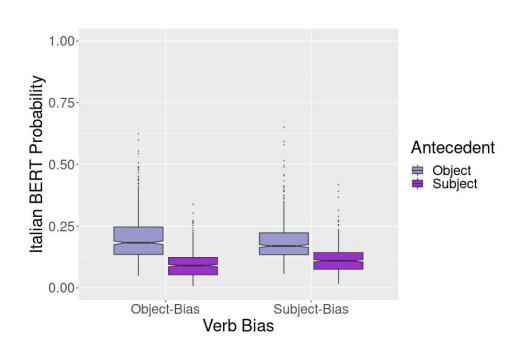


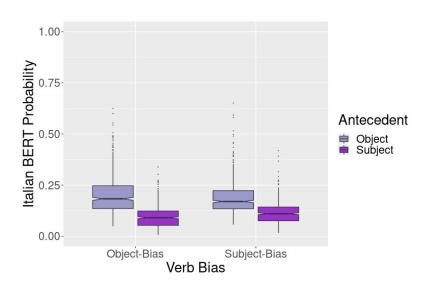
Spanish BERT partial? IC behavior

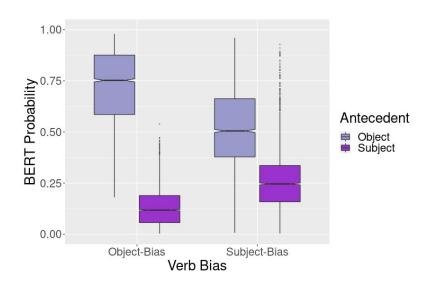












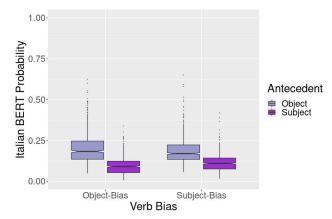
Italian

English

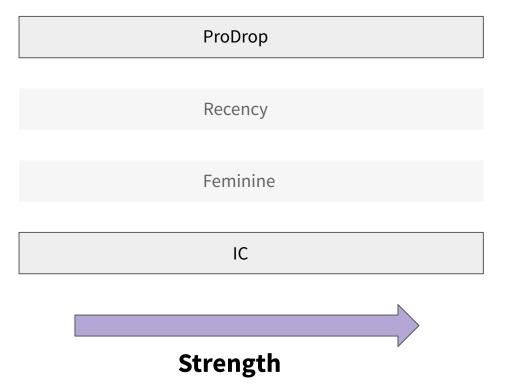
Why aren't we learning IC in Spanish & Italian

- IC is not the only process affecting pronouns
- ProDrop: Overt pronouns in subject position are ungrammatical or dispreferred

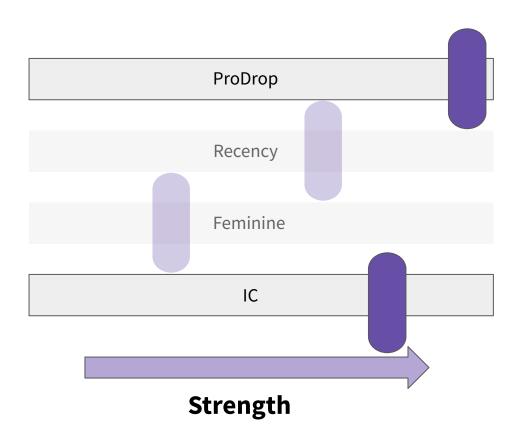
is happy vs. *he is happy



Processes as Constraints



Processes as Constraints



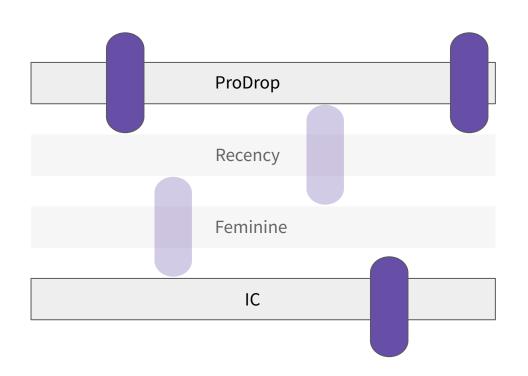
The man admired the woman because __ was there

ProDrop Competes with IC bias

ProDrop outranks IC

Can we promote IC by demoting ProDrop?

Processes as Constraints



The man admired the woman because she was there

Demoting ProDrop with Fine-tuning

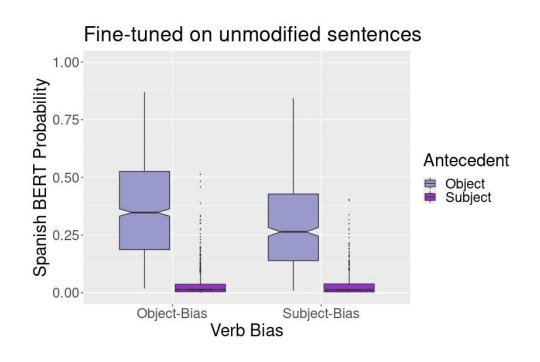
Method: Add pronouns to Spanish/Italian ProDrop sentences

UD datasets (AnCora Spanish, Italian ISDT and VIT)

- Find finite verbs w/o nsubj relation, filtering out test IC verbs
- Added a pronoun matching the verb's person and number
- Resulted in 4000 Spanish sentences (~3500 he/she)
 4600 Italian sentences (~2000 he/she);
 0.005% of original training data
- Fine-tuned Spanish and Italian BERT for 3 epochs (Ir=5e-5)

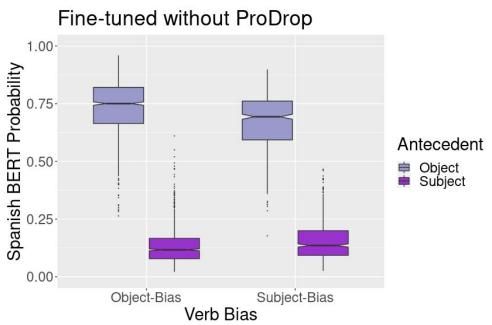
Spanish Baseline

Unmodified sentences



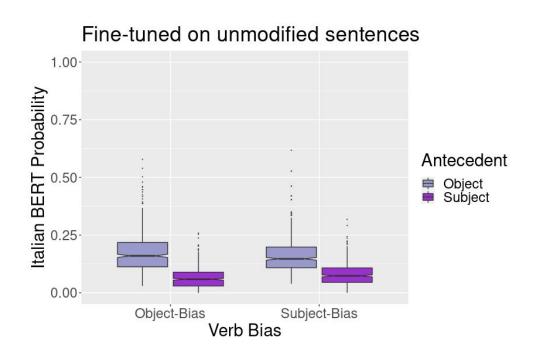
Spanish Fine-tuned

Sentences without ProDrop



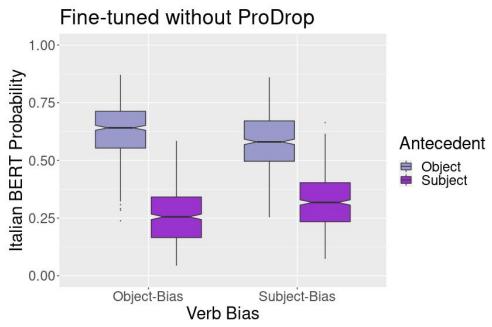
Italian Baseline

Unmodified sentences



Italian Fine-tuned

Sentences without ProDrop



Summary

- Standard behavioral probing: IC is only learned by English models
- In fact, Spanish and Italian models also learn IC but it conflicts with ProDrop
- Removing ProDrop via fine-tuning on a small number of ProDrop violations revealed IC knowledge
 - We explicitly train on data for a process we are **not** testing (i.e. we are not training on IC data)

Conclusion

Adaptation priming is effective for:

Better text predictions

Better human predictions

Probing representations

- Priming can probe feature clusters and constraint/feature rankings
- In addition to single phenomena (usually English)
 need to study interactions (signals compete)

Give it a try!

Thanks!











C.Psyd



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